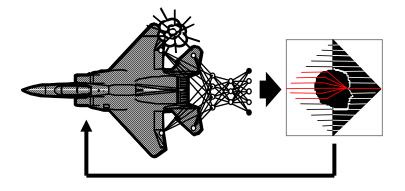




#### Intelligent Control Approaches for UAVs



#### K. KrishnaKumar

NeuroEngineering Laboratory NASA Ames Research Center

Presented at UAV-MMNT03



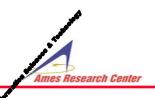


#### **Presentation Outline**



Intelligent Control Background

• Intelligent Flight Control Research @ NASA Ames





# Intelligent Control Background

- What are intelligent systems
- What is intelligent control
- -Intelligent control architectures





# **Defining Intelligent Systems**



- An Intelligent System is one that exhibits any of the following traits:
  - ✓ Learning
  - ✓ Adaptability
  - ✓ Robustness across problem domains
  - ✓ Improving efficiency (over time and/or space)
  - ✓ Information compression (data to knowledge)
  - ✓ Extrapolated reasoning

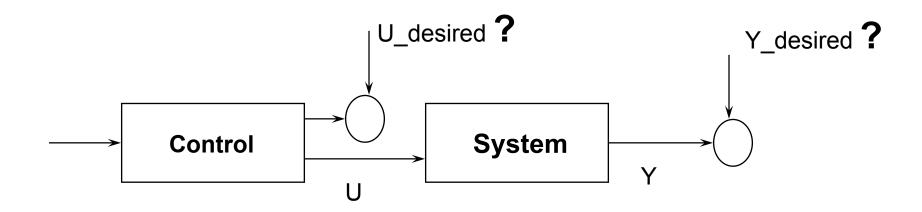
IS is seen as Rationalistic AI: Intelligence for doing the right thing





#### Intelligent Control





#### Two Error Signals are needed:

- 1. System Performance Error Signal
- 2. Control Error Signal





#### Questions



How do we say that one controller is more intelligent than the other?

Can the intelligence be improved?

Can intelligence be measured?

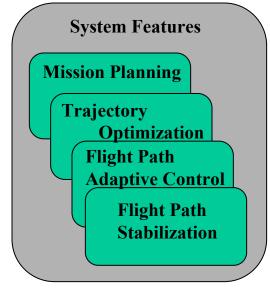
**Answer: Levels of Intelligent Control** 

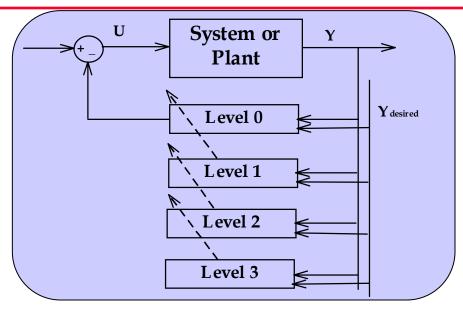




# Levels of Intelligent Control



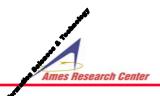




Lev	Self improvement of:	Description
0	Tracking Error (TE)	Robust Feedback control (Error tends to
		zero).
1	TE + Control Parameters	Robust feedback control with adaptive
	(CP)	control parameters (error tends to zero for
		non-nominal operations; feedback control
		is self improving).
2	TE + CP + Performance	Robust, adaptive feedback control that
	Measure (PM)	minimizes or maximizes a utility function
		over time (error tends to zero and a
		measure of performance is optimized).
3	TE+CP+PM+ Planning	Level 2 + the ability to plan ahead of time
	Function	for uncertain situations, simulate, and
		model uncertainties.

K. KrishnaKumar NeuroEngineering Lab

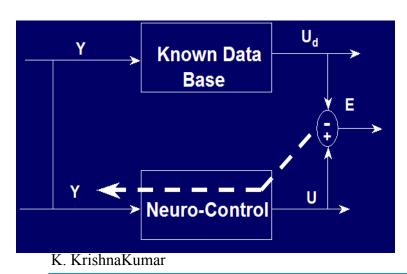


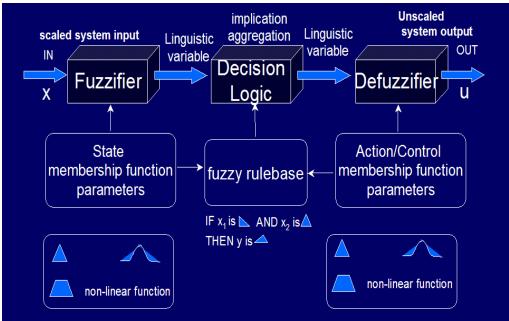




#### **▶** Level 0: Robust stabilization

- Gain Scheduling
- Supervised neuro-control
- Fuzzy control
- Mimic a controller
- Implicit Control



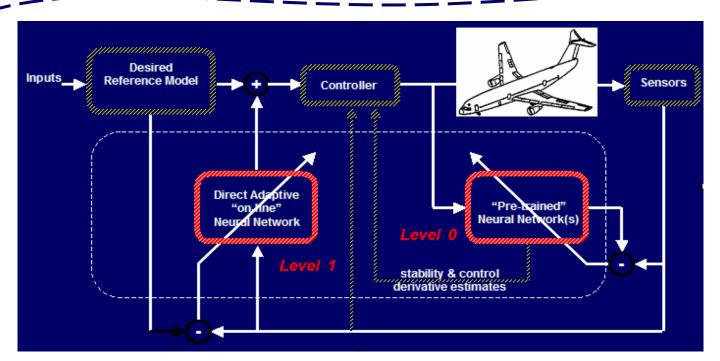




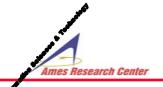


#### **▶** Level 1: Adaptive Control

- Learn Systems and Controller Parameters
- Neural adaptive Control
- Adaptive inverse Control
- Approximate Controller error signal



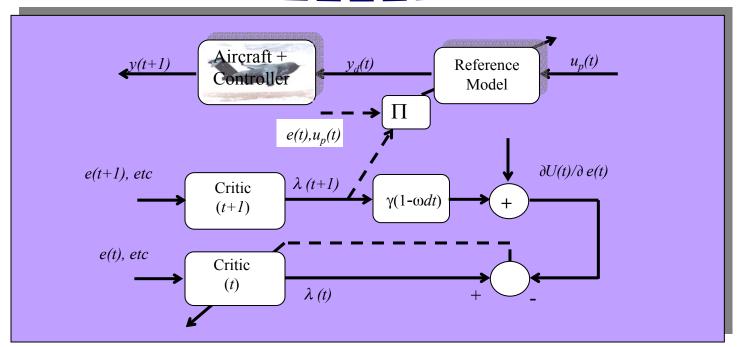






#### **▶** Level 2: Optimal Control

- Reinforcement Learning
- Control Allocation
- Dynamic programming
- Linear Adaptive Critics
- Non-linear Adaptive Critics



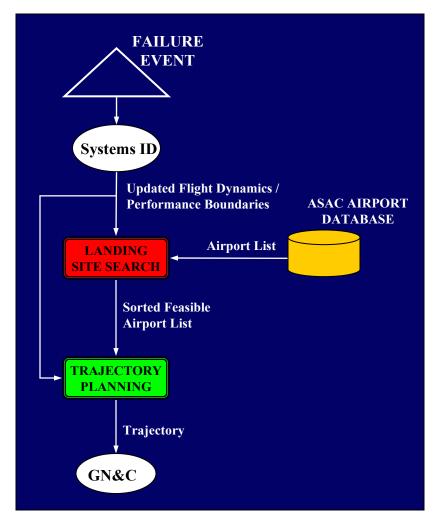






#### **▶** Level 3: Planning Control (More AI-like)

- Strategic Planning
- Strategic search
- Mission Planning
- HTN: hierarchical task network
- Production-based cognitive architectures
- Decision-theoretic (MMDP)
- Etc..

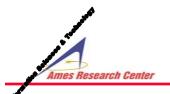








# NASA Ames Intelligent Flight Control Applications



# Manned Aircraft Objectives



Develop flight control technologies that can automatically compensate for problems or failures when they occur

Develop these technologies and capabilities in a generic sense so that they can be applied to different vehicle classes

#### **Application Platforms**

- B 757 class aircraft Simulation only
- F-15 In Flight test
- C-17 Flight tests in 2004

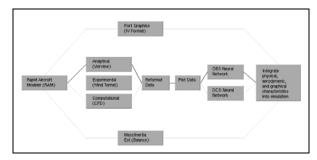


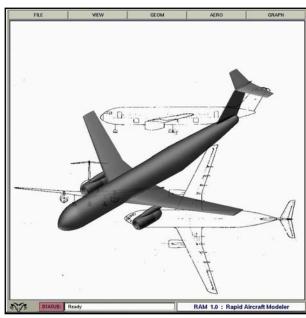


#### **Pre-Trained Neural Networks**

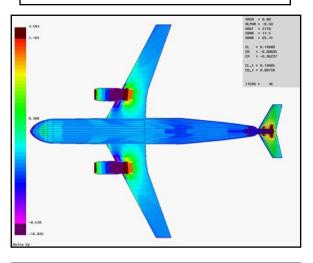


Step 1 Integrated Vehicle Modeling Env. Rapid Aircraft Modeler (RAM)





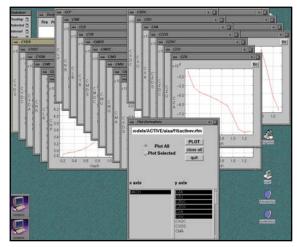
#### Step 2 Vortex Lattice Code (VORVIEW) Mass/InertiaEstimates (Balance)

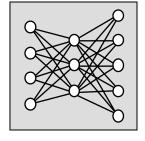


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	L. E. F	MEEP		2.00	20.00	0.00	0.00	(DEC.)
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	TIP T/C			0.06	0.06	0.06	0.00	
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#### Step 3 Levenberg Marquardt neural net Optimal

Pruning Algorithm

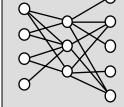












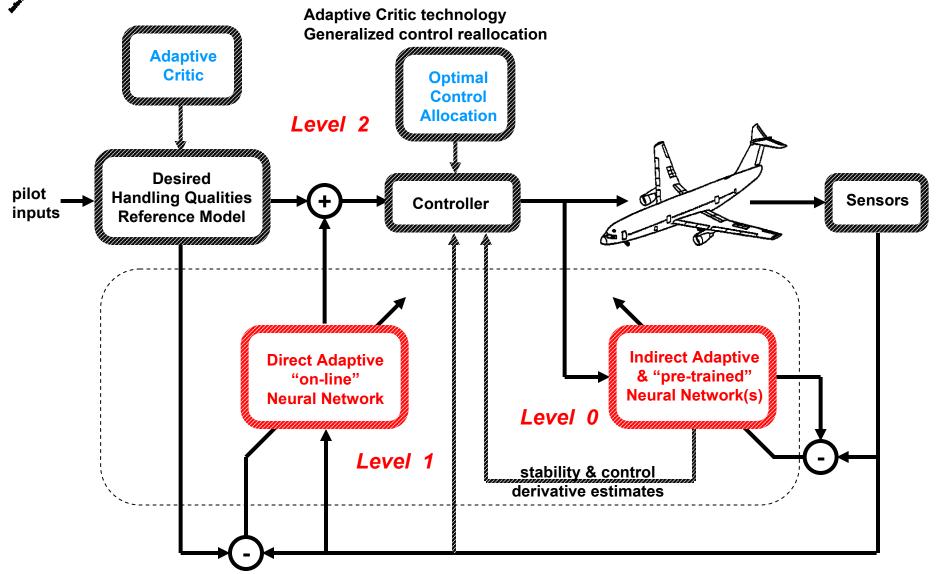
K. KrishnaKumar

NeuroEngineering Lab



# Neural Flight Control Architectures





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# Ames Research Center

# Level 1 Adaptive Control Equations



**Plant:** 

$$\ddot{x} = f(\dot{x}, x, \delta)$$

Linear approximation:

$$\ddot{x} \cong A\dot{x} + B \delta$$

Control law design:

$$\delta = B^{-1} (\upsilon - A\dot{x})$$

**Closed loop:** 

$$\ddot{x} = f(\dot{x}, x, \delta) = \upsilon + \widetilde{f}$$

**Inversion error:** 

$$\widetilde{f} = f - \upsilon = f(\dot{x}, x, \delta) - (A\dot{x} + B\delta)$$



## Level 1 Control Equations



#### Provide compensation for the inversion error by design of $\mathcal{D}$

$$v = v_0 - v_{AD}$$

 $\mathcal{U}_0$  is designed as output of a linear controller, e.g. "PI" control.

$$\nu_0 = \ddot{x}_c + K_p (\dot{x}_c - \dot{x}) + K_I (x_c - x);$$

 $\mathcal{U}_{AD}$  is the adaptive control



## Level 1 Control Equations



#### Rewrite

$$\widetilde{x} = (x_C - x)$$
 and  $e = \begin{bmatrix} \widetilde{x} \\ \dot{\widetilde{x}} \end{bmatrix}$ 

With 
$$a = \begin{bmatrix} 0 & 1 \\ -K_D & -K_P \end{bmatrix}$$
 and  $b = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$ 

We have the tracking error dynamics as:  $\dot{e} = a \ e + b(v_{AD} - \widetilde{f})$ 

#### **Neural Network Input Map:**

$$U_{AD} = W^T \beta(x, V)$$
 for sigma-pi NN

$$\nu_{AD} = W^T \Phi(x, V)$$
 for RBF NN

# Level 2: Optimal Control Allocation



- When to allocate?
  - Control limit violation
  - Rate saturation
  - Control failure
- How to allocate?
  - Optimal allocation using Linear Programming
    - Conventional hierarchy
    - Best available hierarchy

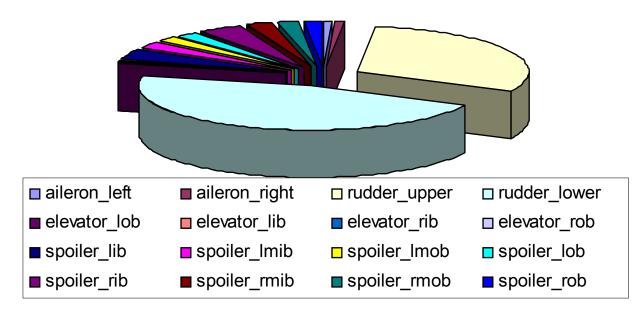




# Example Aerodynamic Control Authority

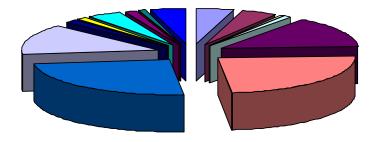


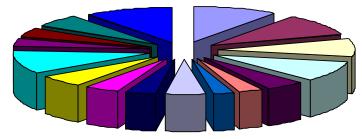
#### **Directional Authority**



#### **Pitch Conrol Authority**

#### **Roll Control Authority**





NeuroEngineering Law

12. 12110111111122



# **Linear Programming Formulation**



Dynamic System is defined as

$$[\dot{X}] = f(X) + [B][u] + f_{trim}$$

Let us write [B]u as

$$\begin{bmatrix} B_{UU} & B_{UL} \end{bmatrix} u_U \\ B_{LU} & B_{LL} \end{bmatrix} u_L + \Delta u_L \end{bmatrix} = \begin{bmatrix} B_{UU} & B_{UL} \end{bmatrix} u_U \\ B_{LU} & B_{LL} \end{bmatrix} u_L \end{bmatrix} + \begin{bmatrix} B_{UU} & B_{UL} \end{bmatrix} 0 \\ B_{LU} & B_{LL} \end{bmatrix} \Delta u_L \end{bmatrix}$$

 $u_{II} = \underline{\text{Unlimited}}$  Control Vector from Dynamic Inverse

$$u_L + \Delta u_L = \underline{\text{Limited}}$$
 Control Vector from Dynamic Inverse



# L P Formulation (cont'd)



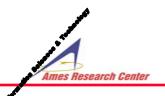
What we need is help from Unlimited Control 
$$\begin{bmatrix} B_{UU} \Delta u_U \\ B_{LU} \Delta u_U \end{bmatrix} = \begin{bmatrix} B_{UL} \Delta u_L \\ B_{LL} \Delta u_L \end{bmatrix}$$

Let us now define a control reallocation matrix  $[\lambda]$  such that

$$\begin{bmatrix} \Delta u_U \end{bmatrix} = \begin{bmatrix} \lambda \end{bmatrix} \begin{bmatrix} \Delta u_L \end{bmatrix} \quad \Longrightarrow \quad \begin{bmatrix} B_{UU} \\ B_{LU} \end{bmatrix} \begin{bmatrix} \lambda \end{bmatrix} = \begin{bmatrix} B_{UL} \\ B_{LL} \end{bmatrix}$$

Define a linear relationship  $|\alpha| |\lambda| = |\beta|$ 

$$\left[ \alpha \right] \left[ \lambda_1 \quad \lambda_2 \quad . \quad . \quad \lambda_m \right] = \left[ \beta_1 \quad \beta_2 \quad . \quad . \quad \beta_m \right]$$



# LP Formulation (Cont'd)



$$\min_{\lambda_i} (w_i^T \lambda_i)$$

Subject to

$$\left[\alpha\right]\left[\lambda_i\right] \leq \left[\beta_i\right]$$
 and  $0 \leq \lambda_i \leq \lambda_{\max}$ 

Example: 4 control inputs

$$[W] = \begin{bmatrix} w_{11} & w_{12} & w_{13} & w_{14} \\ w_{21} & w_{22} & w_{23} & w_{24} \\ w_{31} & w_{32} & w_{33} & w_{34} \\ w_{41} & w_{42} & w_{43} & w_{44} \end{bmatrix} = [w_1 \quad w_2 \quad w_3 \quad w_4]$$



# Conventional & Best Hierarchies



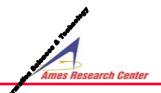
	Elevator	Left Aileron	Right Aileron	Rudder
Elevator	Primary	Secondary	Secondary	
Left Aileron		Primary	Secondary	Tertiary
Right Aileron		Secondary	Primary	Tertiary
Rudder		Secondary	Secondary	Primary

#### Conventional

$$[W]^T = \begin{bmatrix} * & 1 & 1 & 100 \\ 100 & * & 1 & 10 \\ 100 & 1 & * & 10 \\ 100 & 1 & 1 & * \end{bmatrix}$$
 
$$[W]^T = \begin{bmatrix} * & 1 & 1 & 100 \\ 100 & * & 1 & 1 \\ 100 & 1 & * & 1 \\ 100 & 1 & 1 & * \end{bmatrix}$$

#### Best

$$[W]^T = \begin{bmatrix} * & 1 & 1 & 100 \\ 100 & * & 1 & 1 \\ 100 & 1 & * & 1 \\ 100 & 1 & 1 & * \end{bmatrix}$$



# Implementation



• Primary Cost based on "surface"

$$\frac{\min}{u}(w^T u)$$

Auxiliary Cost based on "axis error"

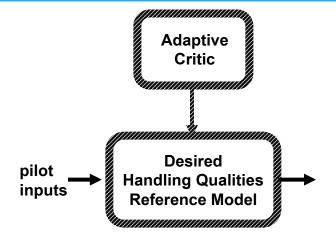
$$\frac{\min}{u}(c^T e)$$



#### Level 2 Controller



# Reference Model Adaptation using an Adaptive Critic





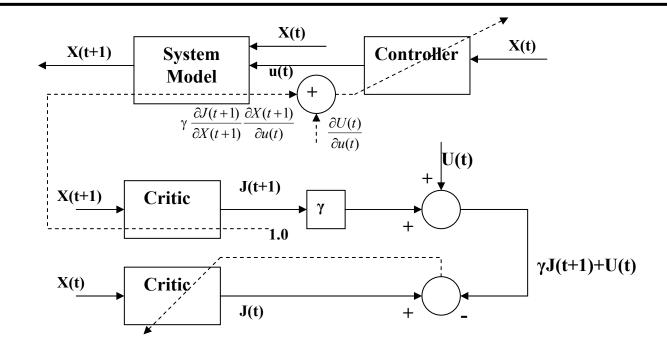


## Adaptive Critic



Adaptive critic designs have been defined as designs that attempt to approximate dynamic programming.

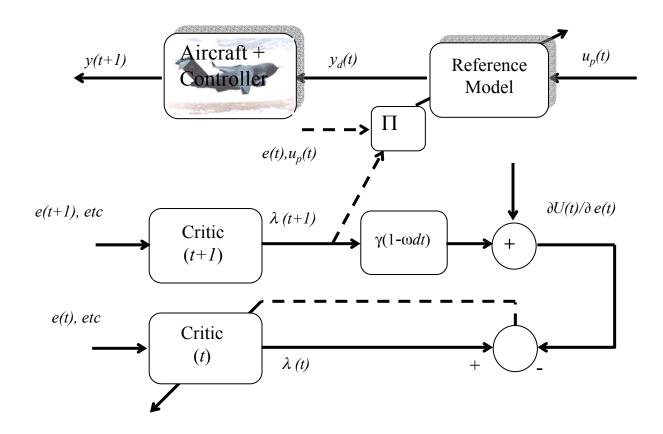
$$J(t) = \langle \gamma J(t+1) \rangle + \min_{u} U(t)$$

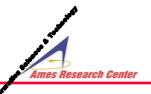




#### Level 2 Control

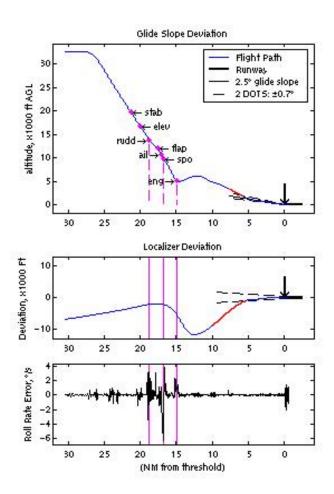


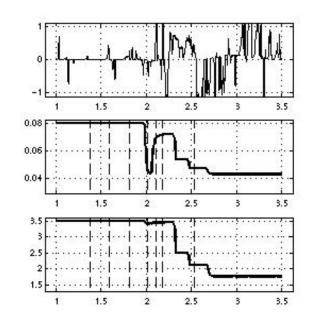




#### Results for Series of Failures







During tactical descent (failures on one side)

- · 23,000': Stab frozen at trim
- · 20,000': 2 Elevators frozen at 0 deg.
- · 17,000': Upper rudder hard over
- · 15,000': Outboard flap fails retracted
- · 14,000': Aileron frozen at 0 deg.
- · 13,000': Two outboard spoilers frozen at 0 deg.

When engines come out of reverse: Outboard engine seizes



# Ames Research

# Intelligent Maneuvering of UAVs



#### •Goals

-Provide increasingly higher levels of automation, capable of responding to changing goals and objectives, while taking corrective actions in the presence of internal or external events.

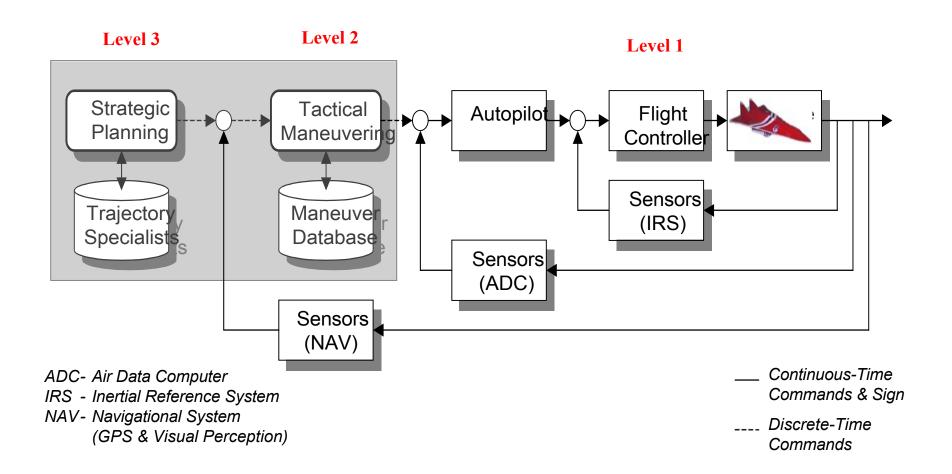
-Allow pilots, ground-based operators or **autonomous executives** to defer the responsibilities of performing and supervising tasks, to focus on managing goals and objectives.





## Intelligent Maneuvering of UAVs

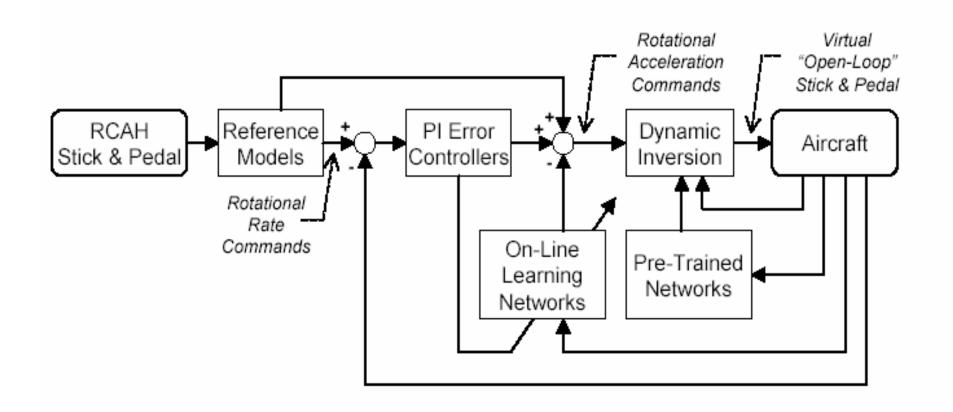






# Flight Controller







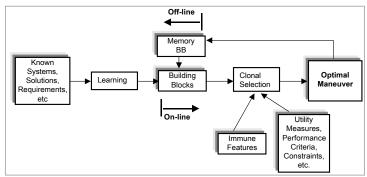
#### **Tactical Maneuvering**



# Performs time-critical flight path operations, which includes aggressive maneuvers in the presence of unexpected obstacles.

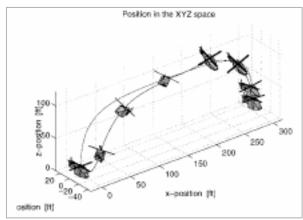
- •Inputs
  - -Commands
    - •Reference Targets / Trajectory
    - Performance Parameters
  - -Awareness
    - •Threat Detection (eg. TCAS, GCAS)
    - •Vehicle Performance Models
- Outputs
  - -Maneuver Sequence
    - Control Law Specific Modes & Targets
    - •Transition Criteria
- Maneuver Selection Specialists
  - -Immunized Maneuver Selection
  - -Heuristic-Based TSP Maneuver Selection
- Maneuver Database
  - -Elements & "Canned" Sequences

#### Immunized Maneuver Selection



Krishna Kumar

#### Model Predictive Take-off and Landing



Eric Wan NeuroEngineering Lab

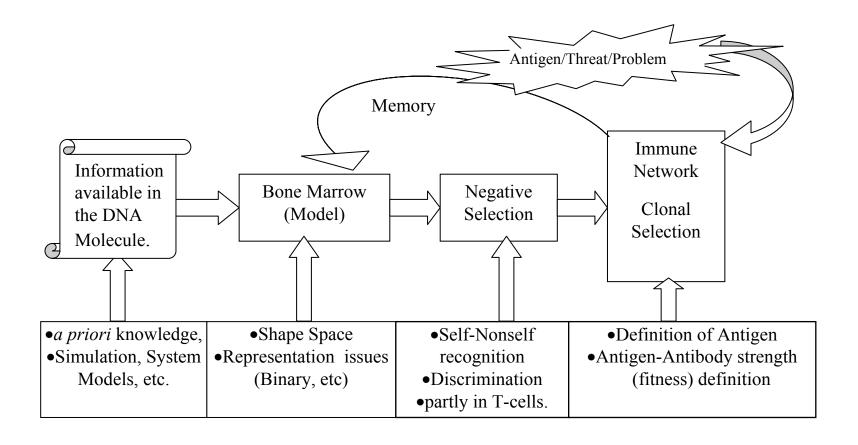
K. KrishnaKumar





# A system-level description of the Immune System Metaphor







#### Tactical Maneuvering Database



Contains general and aircraft specific maneuvering database elements, each corresponding to associated control laws. Pre-canned maneuver sequences represent domain expertise.

- •Elements
  - -Control Law
    - Mode & Target Definition
  - -Aircraft Specific
    - •Flight Envelope Validation Logic
  - -Specifications
    - •Closed-Loop Predictive Models  $(x_0, ..., x_f)$
    - •Resource Allocation Table (e.g. lat, lon, ped, thr/col)
- Sequences
  - -Elements
    - •Specified Parameters / Arguments
  - -Transition Criteria / Termination Logic
    - Time-Based and/or Condition-Based
  - -Interrupts
    - •Abort Conditions & Abort Sequence

#### Bank to Turn Element

Heading Select (coord. turn)

Mode: HDGSEL

Target: Heading = [arg1] deg Envelope: IAS > 180 kts,  $|\theta| < ...$ Model:  $\varphi_o/\varphi_i = \tau/(\tau s+1)$ ,  $φ'_{max} = gcos(θ)sin(φ_{max})/v_t$ RAT: LAT/PED

#### Bank & Pull to Turn Sequence

Bank Left: 0

Normal Accel. (speed control)

Bank Right: +90

Mode: BANKSEL

Target: Bank = 90 deg, Vz = Vz<sub>0</sub> Envelope: mach > 0.4,  $|\alpha| < ...$ 

Model:  $\phi_0/\phi_i = \tau/(\tau s+1)$ ,

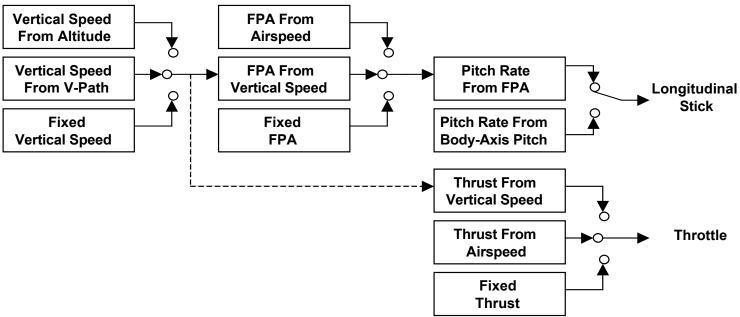
 $\phi'_{\text{max}} = p_{\text{max}}$  $Vz = Vz_0$ 

**RAT: LAT/PED** 



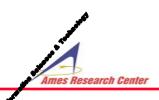
#### Autopilot System (Example)





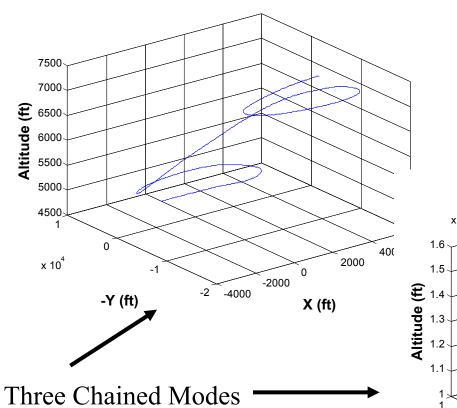
- •Longitudinal Modes
  - -Pitch, Nz, AoA, FPA; Mach, IAS, Vertical Speed; Vertical Path, Altitude
- Thrust Modes
  - -Mach, IAS, Vspd, Thrust; Vertical Path, Altitude, FPA
- Lateral Modes
  - -Bank, Roll Rate; Heading, Track; Lateral Path
- Directional Modes
  - -Sideslip, Ny, Heading

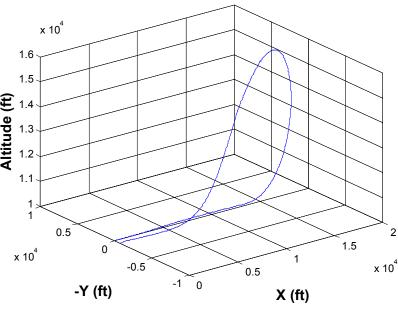




#### Results











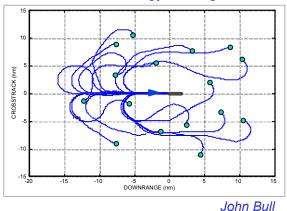
# Strategic Maneuvering



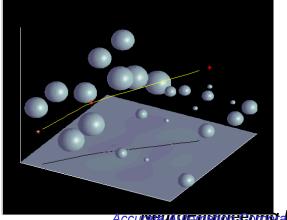
Performs long-term planning that meets dynamic mission goals and objectives, within mission constraints and performance limitations.

- •Inputs
  - -Goals
    - Cost Function
    - Mission Constraints
  - -Awareness
    - •External Obstacles (weather, terrain, ...)
    - •Internal Health & Performance Limitations
- Outputs
  - -Extended Flight Plan
    - •Waypoints / Reference Trajectory
    - Performance Parameters
    - •Configuration Schedules
- •Trajectory Specialists
  - -Energy Management Guidance
    - •Tear Drop, Low-Altitude, Enroute
  - -Evolutionary Navigation





Obstacle Avoiding Evolutionary Navigation





# 'Optimal Way Point Computation Around Obstacles Using Evolutionary Algorithms



#### **➤The Algorithm:**

- >Step 1: Determine the obstacles that are in the path of the flight
- ➤ Step 2: Place the waypoints for the aircraft on the circumference of the obstacles
- >Step 3: Compute the path between the start and the end using the waypoints.
- >Step 4: Compute a fitness function
- >Step 5. After "n" iterations the best set of waypoints defines the navigation path.





#### Demo





#### Intelligent Control for BEES



Mars

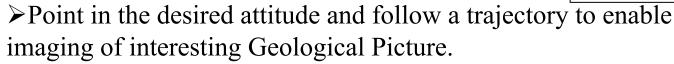
Flver

Exploration of Mars using Free-flyers with sensors inspired by

Nature

#### Controller Objectives:

Maintain safe distance from the Lander and ensure local stability.



- ➤ Optimize long-term and short-term goals, such as minimization of fuel (long-term) and avoid collision with the **Lander** (short-term)
- React to changing environments by adapting the control functionality



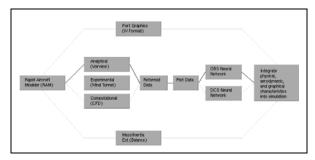
Mars Lander

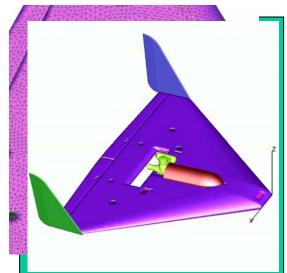


#### **Pre-Trained Neural Networks**

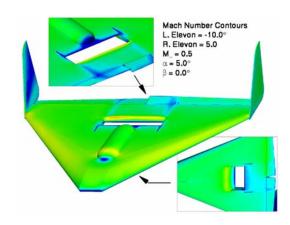


Step 1
Integrated Vehicle Modeling Env.
CAD Designs



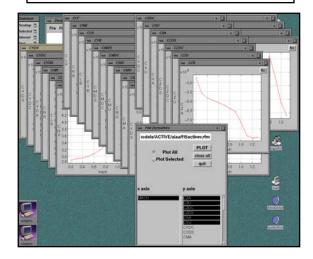


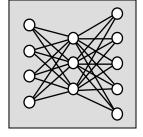
#### Step 2 Cartesian Euler Code (CART3D)



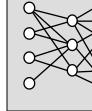
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						422.00	0.00	(FT.)
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	FOOT CH	ORD		8.20	6.85	6.85	0.00	(PT.)
	TIP ONO	PD		8.20	5.00	6.85	0.00	(FT.)
	L. E. S	MEEP		2.00	20.00	0.00	0.00	(DBC.)
	ROOT T/	C		0.00	0.06	0.06	0.00	
	TIP T/C			0.06	0.06	0.06	0.00	
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# Step 3 Levenberg Marquardt neural net Optimal Pruning Algorithm



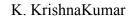










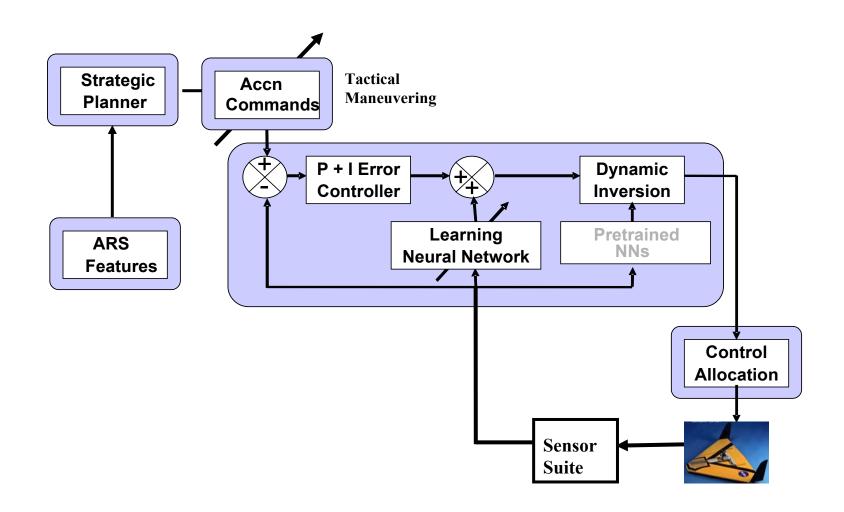


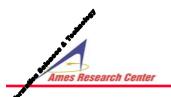




#### Level 2 Architecture







## Concluding Remarks



- ✓ Intelligent control comes in many flavors
- ✓ Levels of Intelligent Control is one way of quantifying the roles of Intelligent control
- ✓ Intelligent control architectures allow for fast prototyping
- ✓ Intelligent control architectures can guarantee inner-loop stability
- ✓ For UAV application, intelligent control provides a robust way to accommodate any outer-loop architecture for planning, etc.